Monitoring of Structural Performance

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David Hester[1], James Brownjohn[1]
[1]Vibration Engineering Section, College of Engineering Mathematics and Physical Sciences, University of Exeter, North Park Road Exeter, EX4 4QF
email: d.hester@exeter.ac.uk, j.brownjohn@exeter.ac.uk

ABSTRACT: Bridges are a critical element of the European transport network and therefore their effective management is important to the functioning of the European economy. Managing bridge assets is a very challenging task both logistically (i.e. there are thousands of bridges distributed across a vast network) and financially (budgets for monitoring and maintenance are limited, and in many cases decreasing). Management involves making decision about the structure and in any system, the quality of decision making is related to the quality of information available. For the vast majority of bridges the information available is visual in nature and therefore the quality of information is significantly dependant on the skill/knowledge of the inspector. Even when there is electronic monitoring data available for a bridge one of the great difficulties is that the data is not easily interpreted. This is because bridges are complex systems whose response signatures are significantly affected by external factors such as temperature or traffic load and as a result it can take years to learn the bridge's 'normal' response envelope. Bradly speaking it is this complexity that makes bridge SHM more challenging than SHM in mechanical systems. Mechanical systems tend to have a relatively narrow response signal under 'normal' monitoring conditions which makes the detection of anomalies easier than is the case for bridges. The research project (*Monitoring of Structural Performance*) presented in this paper aims to contribute to addressing the above challenge by developing a decision support system to assist bridge operators make decisions about their structures. The project aims to do this by making use of physics-driven and data-driven modelling methods to produce metrics that are useful for decision support.

KEY WORDS: Bridges; Monitoring; SHM; Decision support.

1 INTRODUCTION

Transportation infrastructure is crucial to the functioning of a developed economy. For a large trading block such as the European Union this infrastructure is especially important as it facilitates trade across the entire Euro zone. Continued growth in Europe needs a functioning low cost transport infrastructure. Bridges are a key element of the transport network as they are multi modal in nature i.e. they are relevant to road, rail and (even) waterway transport.

However, bridges deteriorate over time and there is no easy way to measure this. The cost of repairing faults in a bridge, once the fault starts to approach criticality, is enormous both in terms of cost and traffic delays. For example, the American Association of State Highway and Transport Officials (ASSHTO) produced a report in 2007 titled 'Bridging the Gap' [1] which estimated that it would cost $140 billion to repair every deficient bridge in the US. If flaws in a structure could be identified early using Structural Health Monitoring (SHM), the cost of repair could be vastly reduced and congestion could be minimised through optimised intervention.

Across Europe there are a substantial number of bridges that are vital to the economies they serve, and which, if taken out of commission would have a devastating impact on local, national, and international economies. For example Humber Bridge in the UK (Figure 1) carries 120,000 vehicles per week, if the bridge were closed the detour would add approximately 90km to the original journey and result in substantial congestion.

Figure 1. Humber Bridge, England.

A recent example of the transport chaos that can ensue as a result of the closure of a bridge was the 2011 closure of the Hammersmith flyover due to concerns about the condition of the post tensioning tendons. This closure highlighted the difficulties when there is a lack of prior structural performance track record and means to assess impact of the

discovered damage. In a similar situation the M4 Boston Manor viaduct was closed three weeks before the 2012 Olympics due to discovery of a new crack in a "sensitive location" during minor repairs.
These kinds of shock events highlight the very important and difficult task that bridge/road and rail authorities face. *Monitoring of Structural Performance (MOSP)* aims to contribute to this task by developing a decision support system for bridge management.

2 OVERVIEW OF CHALLENGE

The concept of Structural Health Monitoring (SHM) of physical assets started in the power generation industry in the 1970s. Dimagronas [2] gives a comprehensive review of the evolution of SHM since that time and broadly speaking it has proved to be quite effective for monitoring mechanical systems, particularly rotating machinery. The last quarter of a centenary has seen the same philosophy of instrumentation and monitoring applied to valuable civil engineering assets such as large bridges. For example many of Europe's large bridges (such as the Millau Viaduct) already have instrumentation installed to detect movements. However, for the most part the results for bridge SHM have not been as successful as SHM for mechanical systems. In the opinion of the authors this is primarily due to the fact that broadly speaking it is more difficult to interpret bridge data than mechanical data. For example, within a mechanical system the response signature of given parameter (e.g. strain in a component) is relatively narrow. However, the response signature for a bridge (e.g. strain in a particular component) can vary substantially even under normal operating conditions due to changes in temperature, traffic load and boundary conditions. Therefore typically it takes a long time to learn 'normal' patterns for the bridge and as a result this makes the identification of anomalies difficult.

The ultimate goal of this research is to try and develop a Decision Support System (DSS) for bridge managers, i.e. we want the DSS to output metrics of use for decision making.

For larger bridges (that typically have permanent instrumentation and therefore much data is available) the challenge is to develop a data fusion system capable of interpreting the data and outputting tangible metrics that can be used by bridge managers to make cost effective decisions.

For smaller bridges (no permanent sensor installation) the challenge is to utilise recent advances in sensor technology to collect (limited) data within the financial and logistical constraints that network operators function under but still provide some metrics useful for decision making. It is envisaged that the metrics produced by the DSS will complement the (primarily visual) information that is currently used to make decisions. Essentially we want to see if sensor data can add value to the existing decision making process. The graphic in Figure 2 illustrates the concept.

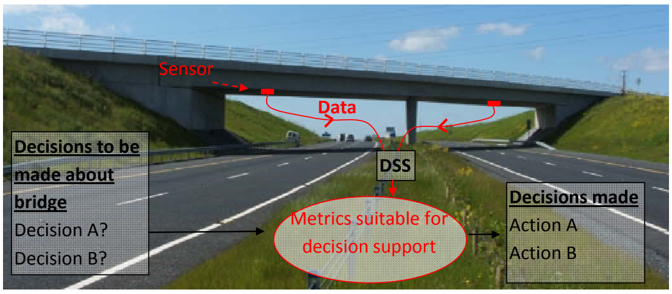


Figure 2. Flow chart showing concept behind DSS.

3 OUTLINE OF PROJECT

Monitoring of Structural Performance (MOSP) will carry out research to try and develop an advanced computerised Decision Support System (DSS) to assist bridge managers in making cost effective decisions. Many of Europe's larger bridges already have instrumentation that provides information on displacement, acceleration, temperature, wind speed, traffic load, etc.. This data can be used as an input to the new system. The objective is to 'fuse' the data in a logical manner i.e. the system will attempt to integrate the disparate pieces of information to form a picture of how the structure is performing. The flow chart in Figure 3 illustrates the concept of the procedure. In the figure a truck is shown crossing a bridge. At the same time the bridge is subject to wind loading and, depending on environmental conditions, it is also affected by temperature fluctuations. Sensors can be used to monitor variables such as temperature, wind speed and bridge acceleration and some sample plots are shown in the second part of the flow chart. The challenge is to fuse this disparate data into a coherent picture to provide information of use for making effective decisions regarding the structure.

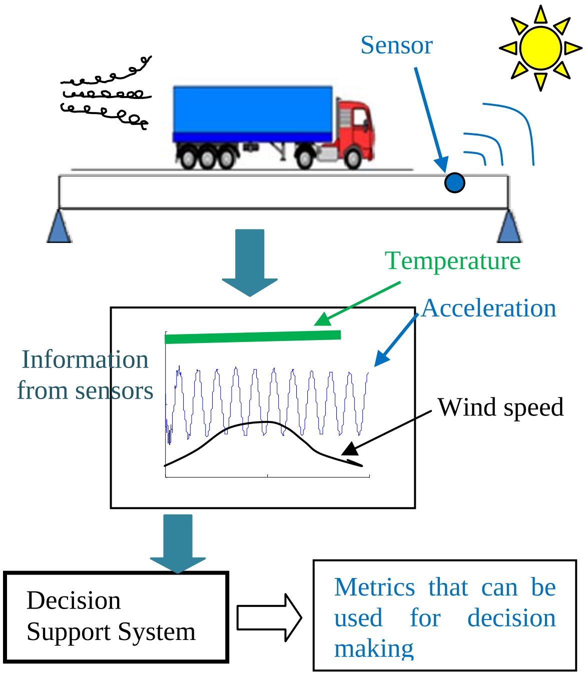


Figure 3. Sequence for using new Decision Support System.

The current state of the art for bridge monitoring techniques can be classified as either **Physics-driven**' or '**Data-driven'**. Table 1 gives a summary of the philosophy behind each of these two techniques and the text following the table gives a literature review.

Table 1. Physics-driven Vs Data-driven

Physics-driven	Data-driven
Physics-based techniques utilise our physical understanding of the system. Equations that define relationships between the different system variables are used to construct numerical models of the system. For example, prepare a finite element model of a bridge and calculate the displacement due to a given load. If the observed displacement due to the same load increases, this could be an indication that the bridge has experienced some damage.	Data-driven approaches are appropriate when the understanding of first principles of system operation is not comprehensive or when the system is sufficiently complex that developing an accurate model is prohibitively expensive. These algorithms are designed to 'learn' characteristics of a time series generated by sensor data during a period called the initialisation phase during which the structure is assumed to behave normally. This phase subsequently helps identify those behaviours which can be classified as anomalous. For example, the displacement of the bridge may be monitored for two years during the initialisation phase. If in subsequent years the displacement is observed to go outside the envelope established during the initialisation phase it indicates that the bridge has experienced some damage.

Physics-based Catbas et al. [3] provide a comprehensive report on applying physics based models to bridges. Numerous researchers have applied physics based models to actual constructed systems, [4,5]. These models are typically used to model the behaviour of the structure under critical loading. They are also used to diagnose the causes of changes in behaviour. For example Teughels and De Roeck [6] use the method to identify structural damage in a Swiss highway bridge. The principal drawback of the approach is that even when the model is tuned using experimental data the behaviours predicted by the updated model may not be correct due to uncertainty and parameter compensation [7]. In recent work Goulet et al. [8] allow for uncertainty in their model(s) and they show that using this approach they were able to falsify the hypothesis that the bridge under investigation was behaving as designed when subjected to ambient vibration inputs.

Data-based Several authors have investigated the use of data based approaches to model structures [9,10]. The primary advantage of these approaches is that they are solely dependant on the data provided, this makes them attractive for the modelling complex phenomena. Posenato et al. [11] describe a typical data based bridge monitoring system. The drawbacks of the data based approach are the length of time needed to train the model and also the difficulty in identifying the effect of individual inputs. For example the deflection of the bridge is larger during the day than at night. This is due to the higher traffic load and the increase in temperature, however it is very difficult to say what portion of the deflection is due to traffic alone.

Both methods (Physics-driven' and 'Data-driven') have strengths and weaknesses so the logical approach is to exploit the advantages of each method by implementing both when monitoring the structure. The objective of MOSP is to integrate the Physics-driven and Data-drive methods into one system that will provide performance prognosis and support decision making. Essentially, both methods will be applied to a given structure and the results from each method will be input into a decision support system (DSS). The DSS will support evidenced based reasoning under uncertainty. A schematic of the procedure is given in Figure 4.

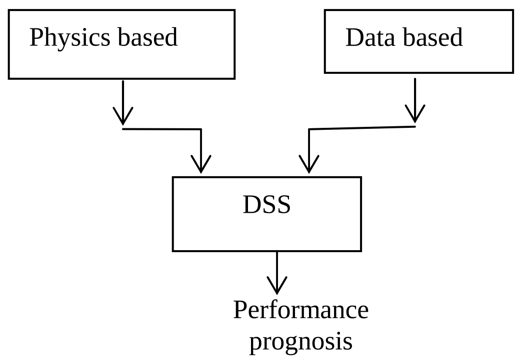


Figure 4. Concept for Decision Support system

Broadly The project is broken into six separate stages.

- Stage1 dialogue with stakeholders to identify desired outputs from DSS
- Stages 2&3 Physics-based modelling
- Stage 4 Instrumentation
- Stage 5 Data-based modelling
- Stage 6 Development of novel DSS

and these are dealt with in the following section.

4 PROJECT STAGES

Stage 1: Talk to stake holders and identify what performance metrics they have faith in. This is a crucial step because it identifies from the outset the outputs we want from the DSS. The stakeholders include bridge operators and road authorities.

Stage 2 conceptualisation of the physical model, in this case a Finite Element (FE) model will be used. Using dimensions measured in the field and any available drawings, the model geometry and element selection for a number of bridges will be prepared. Note at this stage no material properties will be assigned to the model. In relative terms, ascertaining accurate geometric properties for an existing structure is substantially easier than ascertaining accurate material properties. Therefore the material properties will be assigned using a separate process in stage 3. This approach, has previously been used by Exeter's Vibration engineering Section (VES) to prepare the geometric part of the FE model for Tamar Bridge (Figure 5). Tamar is a suspension bridge with a 335 m centre span and it carries approximately 40,000 vehicles per day between Devon in the UK.

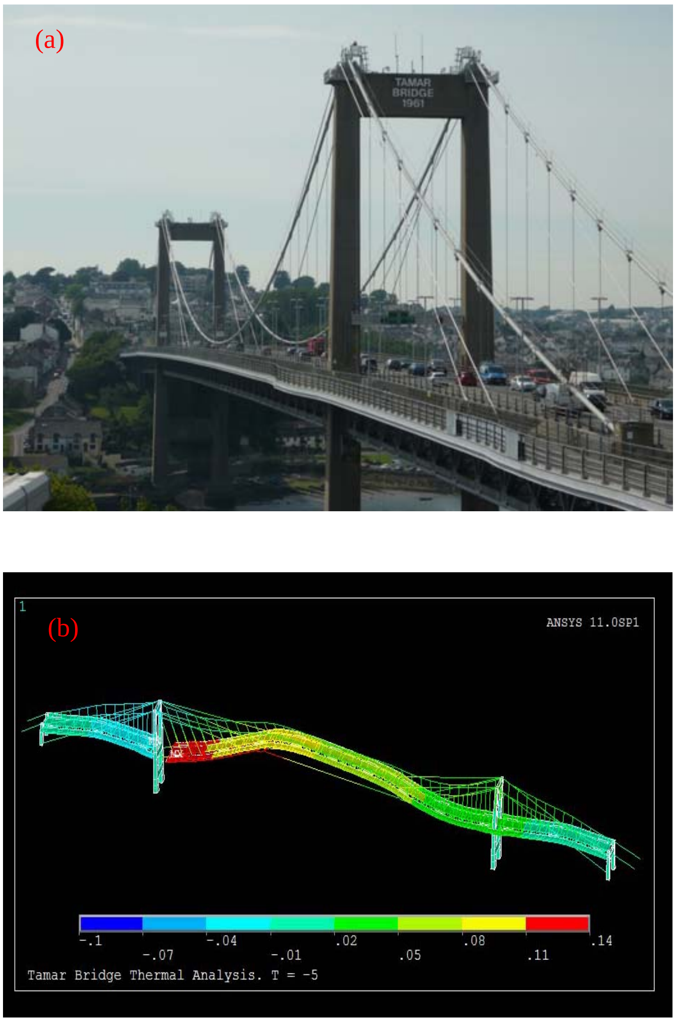


Figure 5. Tamar Bridge; (a) Photograph of structure, (b) Finite element model of structure.

Stage 3 'Model updating' leading to single/multiple physics-based models. Once the geometric part of the model has been established the next step is to assign material properties to the structure. Obviously selecting the correct material properties is crucial if the model is to accurately simulate the behaviour of the real structure. The performance of the model can be checked against measured results and the input properties can be 'updated' using an iterative process so that the outputs of the model match the measured behaviour. This is the traditional approach to tuning a model. However, in work by [8] it is shown that parameter compensation can occur resulting in errors in the models. They found that creating multiple models from a statistical distribution of material properties and then disregarding all the models except the handful that match the observed behaviour worked best.

Stage 4 Instrumentation layout. For long term monitoring the instrumentation design requires the use of methodologies for optimal sensor placement [4]. Variables to be measured include displacement, acceleration and temperature.

Stage 5 Development of new data based systems. Here we take existing data-based systems similar to those described in section 3. However, before applying them to the field data some modifications/improvements will be made to the methods. In particular it is hoped that the following two new features will be introduced to the models:

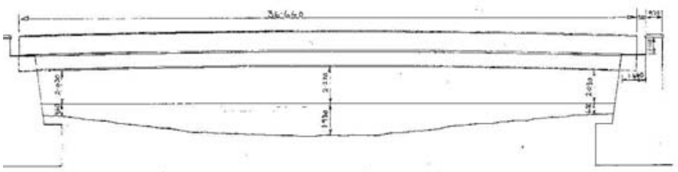
- <u>Adaptive baselines</u>- As described in section 3, when using data-based methods anomalies are detected when the metric being observed goes outside the boundary of what was measured in the initialisation phase. It would be extremely useful if the baseline/threshold values in the data models adapt automatically to new information.
- <u>Single input – Single output load responses</u>- It has already been highlighted that one of the limitations of data-based methods is that the metric being observed is often influenced by several factors, e.g. displacement is influenced by traffic load, wind load and temperature. For future scenario analysis it would be very useful to be able to say what portion of displacement is generated by traffic, what portion is caused by wind and what portion is due to temperature. We hope to be able to develop such a capacity by applying co-integration to the problem. Co-integration has been used in economics and finance since the 1980s since the approach was formalised by Nobel Laureates Engle and Granger. If two or more series are individually integrated (in the time series sense) but some linear combination of them has a lower order of integration, then the series are said to be co-integrated. This process of untangling the various strands is analogous to removing the haystack to find the needle.

Stage 6 Scenario simulation for decision support and prognosis. The aim of the DSS is to use state of the art technology to provide stakeholders with diagnostic and prognostic information shaped to give them optimal decision support. Performance prognosis is likely to prove possible in the coupled data-driven and physics-based approach proposed here via stages 3 and 5. A combination of the two approaches will be used to predict performance for events out of the observed range of experience. It is envisaged that an approach will be adopted similar to that used in the VES Structural Health Monitoring system 'VESHMS' which has been developed to manage existing structures such as Humber bridge in the UK, (span 2,200 m, see Figure 1). This is a data-based system and it operates as described in section 3, so essentially it currently monitors and records what is happening to the bridge. We aim to upgrade this system to include the features described in stages 1-5. It is hoped that the new system will have a new physical-modelling capability as well as improved data-modelling features.

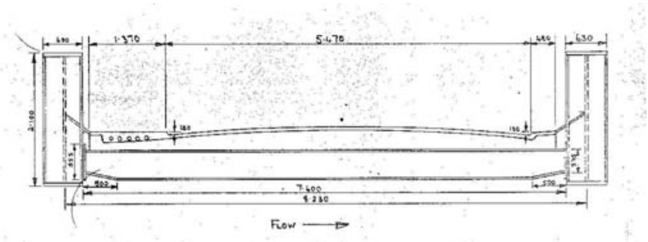
5 EXAMPLE OF MONITORING PERFORMANCE

This section describes an example of quantitative monitoring that was carried on a steel bridge over the River Exe in Devon. The bridge is a single span half through steel bridge on concrete abutments. The clear span between the bearings is 36m, the main beams are 2.1m deep and the flanges are 630mm wide. The bridge runs approximately East-West and Figure 6 is a photo of the North elevation of the bridge. Figure 7shows drawings of the bridge.

Figure 6, North Elevation of bridge.



(a)

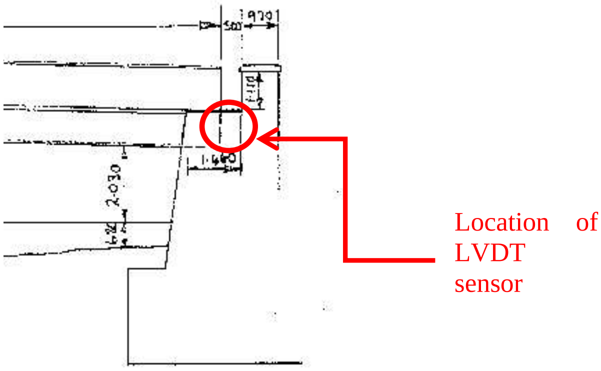


(b)

Figure 7, Steel bridge over the river Exe, (a) Elevation, (b) Section through the deck.

The goal of the study was to examine the regular movements that could be expected from the bridge. Although other measurements were recorded on the day (e.g. bridge accelerations) in this paper we will focus on the range of movement that could be expected from the bearings. Figure 8 shows the expansion joint at the east end of the bridge.

Figure 8, Deck expansion at the east end of the bridge, (this view is looking north).



(a)

Figure 9, Location and arrangement of LVDT sensor (a) Location, (b) Arrangement

The LVDT sensor shown in Figure 9(b) measures the relative displacement between the end of the steel beam and the curtain wall at the back of the abutment. The LVDT is mounted on a retort stand whose base is attached to the end of the steel beam using a magnet. The movement of the joint was observed from 10.00 hours to 16.50 hours. As well as measuring displacement a thermocouple was used to record the temperature at a point on the east end of the main beam on the north side of the bridge. Figure 10 shows the movement between the north beam and the east abutment, this movement is plotted with respect to the left hand y-axis. The figure also shows the temperature of the steel beam at the location described above. The temperature information is plotted with respect to the y-axis on the right hand side. It can be seen in the figure that the temperature of the steel increases from approx. 9.5^{o}C at 10.00 hours to a maximum of 15^{o}C at 14.45 hours and this results in the joint closing by approximately 2.5mm. From 14.45 hours onward the temperature of the steel starts to reduce and the joint starts to open slowly.

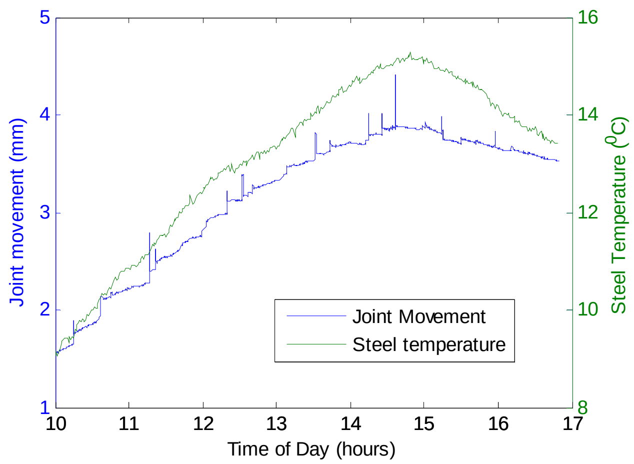


Figure 10, Steel temperature an associated joint movement.

6 CONCLUSIONS

This paper outlines the Marie Curie FP7 Monitoring of Structural Performance (MOSP) research project. The goal of the project is to provide a decision support system for bridge management to assist in providing for reliable and efficient operation of European bridges. The project aims to combine data based and physics based modelling techniques to develop a more holistic approach to bridge monitoring. The outputs from the project should result in enhanced reliability and productivity for bridges on Europe's transport networks.

ACKNOWLEDGMENTS

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REFERENCES

[1] Bridging the Gap (2008), American Association of State Highway and Transportation Officials

[2] Dimagrogonas A.D. (1996) Vibration of cracked structures, *Engineering Fracture Mechanics*, **55** (5): 831-857.

[3] Catbas FN, Kijewski-correa T, Aktan EA (Eds) (2013), Structural Identification of Constructed Systems. Approaches, Methods, and Technologies for Effective Practice of St-Id. Amercian Scoiety of Civil Engineers

[4] Brownjohn, J. M. W. (2003). "Ambient vibration studies for system identification of tall buildings." *Earthquake Engineering and Structural Dynamics*, 32(1)

[5] Farrar, C. & Doebling, S. W. (1998). "Damage detection II: Field applications to large structures." *Proceedings of NATO Advanced Study Instituteon Modal Analysis and Testing*,

[6] Teughels, A.& De Roeck, G. (2004). Structural damage identification of the highway bridge Z24 by FE model updating. *Journal of Sound and Vibration*, 278(3), 589-610.

[7] Goulet JA.; Kripakaran P, Smith IFC (2010). Multimodel structural performance monitoring. Journal of Structural Engineering-ASCE 136(10) p1309-1318.

[8] Goulet JA, 2012, Probabilistic model falsification for infrastructure diagnosis. PhD Thesis. 5417, EPFL.

[9] Chang, C., Chang, T. & Zhang, Q.. (2001). "Ambient vibration of long-span cable-stayed bridge." *ASCE Journal of Bridge Engineering*, 6(1), 46-53.

[10] Zapico, J. L., Gonzalez, M. P., and Worden, K. (2003). "Damage assessment using neural networks." *Mechanical Systems and Signal Processing*, 17(1), 119-125

[11] Posenato, D. Lanata, F, & Inaudi, D. (2008) Model free data interpretation for continuous monitoring of complex structures Advanced Engineering Informatics, 22 p135-144.